## Fermilab Accelerator Physics Center

# Computation of Eigen-Emittances <br> (and Optics Functions!) <br> from Tracking Data 

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- "Express" space-charge modeling (e.g. with MADX beam-beam elements)

does not require knowledge of $\Sigma_{\mathrm{k}}$ in a simple kick-rotate scheme (but does require $\Sigma_{\mathrm{i}}, \mathrm{i}=0, \ldots, \mathrm{k}-1$ )
requires knowledge of $\beta$-functions, with fixed $\beta$-s can be used as a rough approximation
- Muon cooling channel design -
http://map-docdb.fnal.gov/cgi-bin/ShowDocument?docid=4358


## Outline

- How to suppress halo contribution to covariance matrix in a self-consistent way to obtain right sizes for the space charge forces computation? Multidimensional case please!
- Iterative procedure for nonlinear fit of particle distribution in the phase space with a Gaussian or other smooth function.
- How to find the normal mode emittances (eigen-emittances) when optics functions are not known?
- Eigen-emittances as well as optics functions can be determined from the covariance matrix.
- (Extremely fast \& simple!) exponential fit of particle distribution when the optics functions are known - already implemented in MAD-X, but not described anywhere.


## Definitions

Phase space vector:

$$
\underline{z}=\left\{x, P_{x}, y, P_{y}, s-c \beta_{0} t, \delta\right\}
$$

Canonical momenta in units of the reference value $p_{0}=m c \beta_{0} \gamma_{0}$ :

$$
P_{x}=\left(p_{x}+\frac{e}{c} A_{x}\right) / p_{0}
$$

Energy deviation (disguised as momentum)

$$
\delta=\left(\gamma-\gamma_{0}\right) / \beta_{0}^{2} \gamma_{0}
$$

Covariance matrix ( $\Sigma$ - matrix)

$$
\Sigma_{i, j}=\frac{1}{N} \sum_{k=1}^{N} \zeta_{i}^{(k)} \zeta_{j}^{(k)}, \quad \zeta_{i}^{(k)}=z_{i}^{(k)}-\bar{z}_{i}, \quad \bar{z}_{i}=\frac{1}{N} \sum_{k=1}^{N} z_{i}^{(k)}, \quad i=1, \ldots, 6
$$

Basic assumption: particle distribution is a function of quadratic form

$$
\Phi(\underline{\zeta})=\left(\underline{\zeta}, \Sigma^{-1} \underline{\zeta}\right) \equiv \sum_{i=1}^{6} \zeta_{i}\left(\Sigma^{-1} \underline{\zeta}\right)_{i}=\sum_{i, j=1}^{6} \Sigma_{i j}^{-1} \zeta_{i} \zeta_{j}
$$

## How to Suppress Halo Contribution?

And to do this in a self-consistent way?

- a simple heuristic method is to introduce weights proportional to some degree of the distribution function. This leads to an iterative procedure

$$
\begin{equation*}
\bar{z}_{i}=\sum_{k=1}^{N} w_{k} z_{i}^{(k)} / \sum_{k=1}^{N} w_{k}, \quad \zeta_{i}^{(k)}=z_{i}^{(k)}-\bar{z}_{i}, \quad \Sigma_{i, j}=\sum_{k=1}^{N} w_{k} \zeta_{i}^{(k)} \zeta_{j}^{(k)} / \sum_{k=1}^{N} w_{k}, \tag{1}
\end{equation*}
$$

For Gaussian $w_{\Sigma^{1 / 2}}=\exp \left[-\frac{\alpha}{2}\left(\underline{\zeta}^{(k)}, \Sigma^{-1} \underline{\zeta}_{\Sigma^{1 / 2}}^{(k)}\right)\right]$, $\alpha$ being a fitting parameter $(0<\alpha<1)$


Square root of $\Sigma$ from eq.(1) averaged over 25 realizations of 1D Gaussian distribution with $\sigma=1$ as function of the number of particles $N$.


Square root of $\Sigma$ from eq.(1) averaged over 25 realizations of superposition of 1D Gaussian distributions with $\sigma=1(90 \%)$ and $\sigma=3(10 \%)$

This method is imprecise and ambiguous $\Rightarrow$ something based on a more solid foundation is needed.

## Nonlinear Fit of the Klimontovich Distribution

$$
G(\underline{z})=\frac{1}{N} \sum_{k=1}^{N} \delta_{6 \mathrm{D}}\left(\underline{z}-\underline{z}^{(k)}\right) \equiv \frac{1}{N} \sum_{k=1}^{N} \prod_{i=1}^{6} \delta\left(z_{i}-z_{i}^{(k)}\right)
$$

We want to approximate it with a smooth function, e.g. Gaussian

$$
F(\underline{\zeta})=\frac{\eta}{(2 \pi)^{n / 2} \sqrt{\operatorname{det} \Sigma}} \exp \left[-\frac{1}{2}\left(\underline{\zeta}, \Sigma^{-1} \underline{\zeta}\right)\right]
$$

where $\eta$ is the fraction of particles in the beam core, via the minimization problem

$$
\int_{-\infty}^{\infty} \ldots \int_{-\infty}^{\infty}|F-G|^{2} d z_{1} . . d z_{n}=\int_{-\infty}^{\infty} \ldots \int_{-\infty}^{\infty}\left(F^{2}-2 F G\right) d z_{1} . . d z_{n}+\int_{-\infty}^{\infty} \ldots \int_{-\infty}^{\infty} G^{2} d z_{1} . . d z_{n} \rightarrow \min
$$

or the maximization problem for the $1^{\text {st }}$ term in the r.h.s. taken with the opposite sign

$$
\begin{aligned}
& M(\bar{z}, \Sigma, \eta)=\int_{-\infty}^{\infty} \ldots \int_{-\infty}^{\infty}\left(2 F G-F^{2}\right) d z_{1} . . d z_{n}= \\
& \frac{\eta}{(2 \pi)^{n / 2} \sqrt{\operatorname{det} \Sigma}}\left\{\frac{2}{N} \sum_{k=1}^{N} \exp \left[-\frac{1}{2}\left(\underline{\zeta}^{(k)}, \Sigma^{-1} \underline{\zeta}^{(k)}\right)\right]-\frac{\eta}{2^{n / 2}}\right\} \rightarrow \max
\end{aligned}
$$

For $n=6$ there is $n(n+3) / 2+1=28$ fitting parameters - convergence too slow

By differentiating $M(\bar{z}, \Sigma, \eta) \quad$ w.r.t. fitting parameters we recover equations which can be solved iteratively.

For average values of coordinates the equations coincide with heuristic ones with $\alpha=1$

$$
\begin{aligned}
& \bar{z}_{i}=\sum_{k=1}^{N} z_{i}^{(k)} \exp \left[-\frac{1}{2}\left(\underline{\zeta}^{(k)}, \Sigma^{-1} \underline{\zeta}^{(k)}\right)\right] / \sum_{k=1}^{N} \exp \left[-\frac{1}{2}\left(\underline{\zeta}^{(k)}, \Sigma^{-1} \underline{\zeta}^{(k)}\right)\right], \quad \zeta_{i}^{(k)}= z_{i}^{(k)}-\bar{z}_{i} \\
&\left(\frac{1}{N} \sum_{k=1}^{N} \cdots \rightarrow \sum_{k=1}^{N} w_{k} \ldots / \sum_{k=1}^{N} w_{k}\right. \\
&\text { for weighed particles) })
\end{aligned}
$$

We can keep $\eta$ fixed (i.e. set the fraction of particles taken into account)
Then for $\Sigma$ - matrix we get
$\Sigma_{i j}=\frac{1}{N} \sum_{k=1}^{N} \zeta_{i}^{(k)} \zeta_{j}^{(k)} \exp \left[-\frac{1}{2}\left(\underline{\zeta}^{(k)}, \Sigma^{-1} \underline{\zeta}^{(k)}\right)\right]\left(\left(\frac{1}{N} \sum_{k=1}^{N} \exp \left[-\frac{1}{2}\left(\underline{\zeta}^{(k)}, \Sigma^{-1} \underline{\zeta}^{(k)}\right)\right]-\frac{\eta}{2^{n / 2+1}}\right)\right.$
For $\eta \rightarrow 1$ some damping is necessary in $n=6$ case to avoid oscillations:

$$
\Sigma^{(i)}=(1-d) \Sigma^{(i-1)}+d \Sigma^{(\text {formula })}, \quad d \approx 0.8
$$

(Mathematics is presented in the cited MAP note)

## Rigorous Iterative Procedure (cont'd)

We can try to find the optimal fraction of particles $\eta$ for the fit.
From equation $\frac{d}{d \eta} M(\bar{z}, \Sigma, \eta)=0$ we get

$$
\eta=\frac{2^{n / 2}}{N} \sum_{k=1}^{N} \exp \left[-\frac{1}{2}\left(\underline{\zeta}^{(k)}, \Sigma^{-1} \underline{\zeta}^{(k)}\right)\right], \quad \zeta_{i}^{(k)}=z_{i}^{(k)}-\bar{z}_{i}
$$

Equations for average values of coordinates remain the same,
whereas for $\Sigma$ - matrix we obtain expression with an extra factor of 2 (!) compared to the heuristic one

$$
\Sigma_{i j}=2 \sum_{k=1}^{N} \zeta_{i}^{(k)} \zeta_{j}^{(k)} \exp \left[-\frac{1}{2}\left(\underline{\zeta}^{(k)}, \Sigma^{-1} \underline{\zeta}^{(k)}\right)\right] / \sum_{k=1}^{N} \exp \left[-\frac{1}{2}\left(\underline{\zeta}^{(k)}, \Sigma^{-1} \underline{\zeta}^{(k)}\right)\right]
$$

Damping is not necessary in this case.
For $n=6$ in all cases just 20-30 iterations are required to achieve precision $\leq 10^{-6}$, it takes Mathematica $\sim 13$ seconds with $N=10^{4}$ on my home PC. For a Fortran or C code it will be a fraction of a second.


Square root of $\Sigma$ averaged over 25 realizations of 1D Gaussian distribution with $\sigma=1$ as function of the number of particles $N$.
$\delta_{\text {r.m.s. }}$

$\Sigma^{1 / 2}$


Square root of $\Sigma$ averaged over 25 realizations of superposition of 1D Gaussian distributions with $\sigma=1(90 \%)$ and $\sigma=3(10 \%)$
$\delta_{\text {r.m.s. }}$

R.m.s. error in $\Sigma^{1 / 2}$ from above


Projections onto the longitudinal coordinate (left) and $\delta$ (right) of the original particle distribution (cyan bars) and of its Gaussian fit with $\eta=1$ and $\eta=\eta_{\text {fit }}$ (red and blue solid lines respectively).
N.B. Projection of the Gaussian distribution onto the $m^{\text {th }}$ axis in a multidimensional case is proportional to

$$
\exp \left\{-\frac{1}{2}\left(\Sigma^{-1}\right)_{m m} \zeta_{m}^{2}\left[2-\left(\Sigma^{-1}\right)_{m m} \Sigma_{m m}\right]\right\}
$$

## Eigen-Emittances from $\Sigma$ - matrix

With $\Sigma$ - matrix known, how to find the normal mode emittances?

- $\quad \Sigma$ - matrix has positive eigenvalues but they are useless unless the matrix of transformation to diagonal form is symplectic (generally not the case)
- solution suggested by theory developed by V.Lebedev \& A.Bogacz :

Consider a product $\Omega=S \Sigma^{-1}$ of inverse $\Sigma$ - matrix and symplectic unity matrix

$$
\mathrm{S}=\left(\begin{array}{cccccc}
0 & 1 & 0 & 0 & 0 & 0 \\
-1 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 1 & 0 & 0 \\
0 & 0 & -1 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 1 \\
0 & 0 & 0 & 0 & -1 & 0
\end{array}\right),
$$

Matrix $\Omega$ has purely imaginary eigenvalues which are inverse eigen-emittances :

$$
\lambda_{2 m-1}=-\frac{i}{\varepsilon_{m}}, \quad \lambda_{2 m}=\frac{i}{\varepsilon_{m}}, \quad m=1,2,3
$$

(Again, mathematics is presented in the cited MAP note)

## Eigen-Vectors of Matrix $\Omega$

Using real and imaginary parts of eigen-vectors $\underline{v}_{i}^{\prime} \equiv \operatorname{Re} \underline{v}_{i}, \underline{v}_{i}^{\prime \prime} \equiv \operatorname{Im} \underline{v}_{i}$ as columns we can build a matrix:

$$
\mathrm{V}=\left\{\underline{v}_{1}^{\prime},-\underline{v}_{1}^{\prime \prime}, \underline{v}_{3}^{\prime},-\underline{v}_{3}^{\prime \prime}, \underline{v}_{5}^{\prime},-\underline{v}_{5}^{\prime \prime}\right\}
$$

which is symplectic, $\mathrm{V}^{t} \mathrm{SV}=\mathrm{S}$, and brings $\Omega$ to diagonal form:

$$
\mathrm{V}^{-1} \Omega \mathrm{~V}=\mathrm{S} \Xi, \quad \Xi=\operatorname{diag}\left(\frac{1}{\varepsilon_{1}}, \frac{1}{\varepsilon_{1}}, \frac{1}{\varepsilon_{2}}, \frac{1}{\varepsilon_{2}}, \frac{1}{\varepsilon_{3}}, \frac{1}{\varepsilon_{3}}\right) .
$$

The quadratic form $\Phi$ takes the form:

$$
\Phi=\left(\underline{\zeta}, \Sigma^{-1} \underline{\zeta}\right) \rightarrow(\underline{\xi}, \Xi \underline{\Xi})=\sum_{m=1}^{3} \frac{\xi_{2 m-1}^{2}+\xi_{2 m}^{2}}{\varepsilon_{m}}=2 \sum_{m=1}^{3} \frac{J_{m}}{\varepsilon_{m}}, \quad \underline{\xi}=\mathrm{V}^{-1} \underline{\zeta}
$$

## Eigen-vectors provide information on $\beta$ - and dispersion functions :

$$
\begin{gathered}
\beta_{x m}=\left|\left(\underline{v}_{2 m}\right)_{1}\right|^{2}, \quad \beta_{y m}=\left|\left(\underline{v}_{2 m}\right)_{3}\right|^{2}, \quad \beta_{s m}=\left|\left(\underline{v}_{2 m}\right)_{5}\right|^{2}, \quad m=1,2,3 \\
D_{x}=\frac{x}{\delta}=\frac{V_{16} V_{55}-V_{15} V_{56}}{V_{66} V_{55}-V_{65} V_{56}}, \quad D_{y}=\frac{y}{\delta}=\frac{V_{36} V_{55}-V_{35} V_{56}}{V_{66} V_{55}-V_{65} V_{56}} .
\end{gathered}
$$

## Exponential Fit

If the optics is known - and therefore matrix V of eigen-vectors - we can find action variables of particles:

$$
J_{m}=\frac{1}{2}\left(\xi_{2 m-1}^{2}+\xi_{2 m}^{2}\right), \quad \underline{\xi}=\mathrm{V}^{-1} \underline{\zeta}
$$

Ignoring the actual distribution in canonical angles we may look for distribution in the form

$$
F=\frac{1}{(2 \pi)^{3} \varepsilon_{1} \varepsilon_{2} \varepsilon_{3}} \exp \left[-\sum_{m=1}^{3} J_{m} / \varepsilon_{m}\right]=F_{1} F_{2} F_{3}
$$

The fitting is reduced to 3 one-dimensional exponential fits!
Actually it is better to fit the integrated distribution function:

$$
f_{m}\left(J_{m}\right)=\int_{0}^{2 \pi} d \varphi \int_{0}^{J_{m}} F_{m}(x) d x=1-\exp \left[-J_{m} / \varepsilon_{m}\right]
$$

## Exponential Fit (cont'd)

The corresponding part of the Klimontovich distribution (integrated over all other variables)

$$
G(J)=\frac{1}{N} \sum_{k=1}^{N} \delta\left(J-J_{k}\right) \rightarrow g(J)=\int_{0}^{J} G(x) d x=\frac{1}{N} \sum_{k=1}^{N} \theta\left(J-J_{k}\right)
$$

where $\theta(x)$ is an asymmetric Heaviside step-function

$$
\theta(x)=\left\{\begin{array}{cc}
0, & x<0 \\
0<\alpha<1, & x=0 \\
1, & x>0
\end{array} \quad \begin{array}{ll} 
\\
(\alpha=0.1 \text { is slightly better than 1 or } 0)
\end{array}\right.
$$



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## Exponential Fit (cont'd)

Now let us numerate particles in the order of increasing $J_{k}$ take $\log [1-g(J)]$ at all $J=J_{k}$ and equiate it with $\log [1-f(J)]=-J / \varepsilon$

Taking simple average over all particles we get

$$
\frac{1}{\varepsilon}=-\frac{1}{N} \sum_{k=1}^{N} \frac{1}{J_{k}} \log \left[1-\frac{k-1+\alpha}{N}\right]
$$

The only (complicated) thing to do is to re-order the particles!
This formula gives a precise result in absence of halo, but provides only moderate ( $\sim 1 / J$ ) suppression of tails.

